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“Agro-meteorological indices and climate model uncertainty over the UK”

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Abstract Five stakeholder-relevant indices of agro-meteorological change were analysed for the UK, over past (1961–1990) and future (2061–2090) periods. Accumulated Frosts, Dry Days, Growing Season Length, Plant Heat Stress and Start of Field Operations were calculated from the E-Obs (European Observational) and HadRM3 (Hadley Regional Climate Model) PPE (perturbed physics ensemble) data sets. Indices were compared directly and examined for current and future uncertainty. Biases are quantified in terms of ensemble member climate sensitivity and regional aggregation. Maps of spatial change then provide an appropriate metric for end-users both in terms of their requirements and statistical robustness. A future UK is described with fewer frosts, fewer years with a large number of frosts, an earlier start to field operations (e.g., tillage), fewer occurrences of sporadic rainfall, more instances of high temperatures (in both the mean and upper range), and a much longer growing season.

1 Introduction

Decision making for climate change adaptation within the land use sector, and appropriate policy development, requires consideration of relevant environmental pressures (Matthews et al. 2008). The variability of key weather-driven factors, thresholds and tolerances must be identified to form the basis for land manager decision-making (Matthews et al. 2008; McCrum et al. 2009; Rivington et al. 2008a, 2013). In the UK 70 % of land-use is agricultural (DEFRA 2011), only 6.8 % can be classified as “urban” (NEA 2012). When in-urban “greenspaces” and water surfaces are accounted for, the UK’s built environment drops to roughly 2.3 % of land-use, with less than 0.5 % for Scotland (NEA 2012). Land management invested individuals and agencies are thus highly exposed to environmental change (Kane et al. 1992).

Prior studies have focussed largely on metrics of drought (Keyantash and Dracup 2002; Piao et al. 2010) as the most costly form of discrete climate impact (Keyantash and Dracup

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2002) and a potential consequence of projected global temperature and rainfall changes (Kane et al. 1992). There have also been attempts to link metrics of extreme temperature and rainfall, frost and flooding risk (Moonen et al. 2002; Harding 2006), monsoonal rainfall (Krishna Kumar et al. 2004), mean monthly solar radiation and vapour pressure deficit (Fischer et al. 2005), to agricultural climate change impacts. At the regional, farm, and field level, a number of crop-yield modelling tools (DSSAT, EPIC, TEM) have been developed to include climatic forcing and/or the effects of CO₂ increases (Williams et al. 1983; Tubiello and Ewert 2002; Felzer et al. 2004). Understanding regional shifts in agro-meteorological conditions and their contexts helps to identify the possibility of important thresholds being crossed. This then determines when individual or combined land uses are no longer viable in their existing state. Such fundamental indications are vital to the pursuit of optimal management practices and avoiding inappropriate adaptation strategies.

Indicators are more likely to result in active and informed engagement when they have direct relevance to management decisions close to impacted structures and systems (Matthews et al. 2008), in forms that are familiar to scientific, policy, and public community stakeholders (Moser 2009). Matthews et al. (2008) and subsequently McCrum et al. (2009), Rivington et al. (2013), developed a suite of indices in consultation with land managers, demonstrating the value of a social co-learning framework and measures beyond annual or mean monthly climate summaries. Having only analysed a single simulation of regional climate over time (Matthews et al. 2008), however, they did not consider uncertainty in future change.

This paper builds on Matthews et al. (2008), by producing five agro-meteorological indicators from both observations and an ensemble of model simulations. We describe the agro-meteorological indices, the relevant observed and simulated data, and then present results with a set of conclusions. We show potential temporal and spatial variation in some basic, but key, agro-meteorological conditions, before providing some insight into the credibility of the future projections.

2 Methods

2.1 Agro-meteorological indices

Of the agro-meteorological indices developed by Matthews et al. (2008) five were described as ‘very’ or ‘quite’ useful by stakeholder focus groups (Matthews et al. 2008), are easily calculable from a wide number of climate models (i.e., avoid soil-moisture metrics) and have little conceptual overlap (Table 1). The Accumulated Frost Days index has been used to assess aphid risks for crops (Dewar and Carter 1984). The Dry Days index follows a form (days without precipitation over a threshold) that has been in use for drought measurement since 1916. It describes conditions that are necessary for a full estimation of agricultural drought (which relies on soil moisture and vegetation type, both difficult data to acquire over the study region and period) if not sufficient (Heim 2002). Growing Season Length is calculated using a threshold of 5.6 °C, which is approximately the temperature at which grass starts to grow, following Bootsma (1994). Plant Heat Stress describes the temperature above which plants must divert resources from growth towards coping strategies. These range from 45 °C for cotton, down to 25 and 26 °C for cool season pulses and wheat (Wahid et al. 2007). Finally, the Start of Field Operations index was derived from workshops with agricultural stakeholders, and is based on an older index: ‘Tsum200’ (Matthews et al. 2008), referring to the earliest date in a year when a field might be usefully worked. Thermal accumulation of around 200 °C is commonly used by farmers as a ‘rule of thumb’ for when to apply fertiliser to grass.

Table 1 Selected agro-meteorological indices, including type, unit, and means of calculation. PHS is derived from a crop parameter threshold value in the CropSyst model (Stöckle et al. 2003)

Indicator	Type	Units	Metric
1. Accumulated frost (AF)	Degree days	Degree days (°C)	Sum of degree days where $T_{min} < 0.0$ °C
2. Dry days (DD)	Count	Days	Days when $P < 0.2$ mm
3. Growing season length (GSL)			Days when $T_{avg} > 5.6$ °C between start and end of growing season, specified as 5 consecutive days $>$ (start, from 1st Jan) or $<$ (end, from 1st July) 5.6 °C
4. Plant heat stress (PHS)			Days when $T_{max} > 25.0$ °C
5. Start of field operations (SFO)	Date	Day of year	Day when sum of T_{avg} from 1 Jan > 200 °C

T_{min} and T_{max} are minimum and maximum daily temperature (°C) respectively, T_{avg} is the daily mean of those two values (°C), and P is total daily precipitation (mm)

2.2 Data and its evaluation

These indices have been computed using observational E-Obs data (Haylock et al. 2008) for the period 1961–1990 and the HadRM3-PPE set of regional climate model (RCM) simulations (Murphy et al. 2007; Met Office 2012) for the periods 1961–1990 and 2061–2090. The past period is a commonly used reference ‘normal’, established by the WMO. Although agricultural stakeholders normally look 10–40 years ahead (from farm planning to irrigation changes) the future period has been chosen to allow man-made climate variability change (‘signal’) to emerge from ‘internal’ natural variability (‘noise’) in order to make the most of model predictive capacity (Hawkins and Sutton 2012).

The indices have been calculated from data available at a spatial resolution (25 km) useful to land management stakeholders over a target area including the UK and Ireland: 50–59°N, 9.5°W–1.2°E (Fig. 1). Both observational and modelled data afford enough spatial coherence to allow for meaningful map-based analysis, and eleven parallel simulations of the future to allow for uncertainty analysis. Both sets sit upon the same 0.22° ‘rotated pole’ grid, producing even distances between cells at higher latitudes, unlike a ‘regular’ co-ordinate system. Observed and modelled past-period precipitation show similar structural features (scale, grid, topography, etc.) and no notable differences (Fig. 1). For the rest of this study, (bilinearly) interpolated results have been used in the map plots, although no interpolation has been conducted prior to analysis. This allows for ease of interpretation, but has not affected any of the pdfs, averages or trends discussed beyond plots shown in Fig. 3, Online Resources 2 and 3.

2.3 Observed data evaluation

The E-OBS dataset interpolates daily precipitation and temperature information, in a pan-European effort to consistently and coherently aggregate observational meteorological station data (Haylock et al. 2008). When version 7.0 of the gridded product (used here) is tested against UK Met Office (Perry and Hollis 2005) observational data (Hofstra et al. 2009), annual means show strong agreement between the two (temperature correlations of 0.99, 0.85–0.92 for precipitation).

However, inconsistent biases for temperature are evident across the UK (RMSE of up to 0.9°C, for annual data). UK precipitation totals in E-OBS (Fig. 1, left) are generally too low (Hofstra et al. 2009) and are at their least reliable across Western Scotland. That area has few observational stations, significant changes in altitude between stations (making spatial

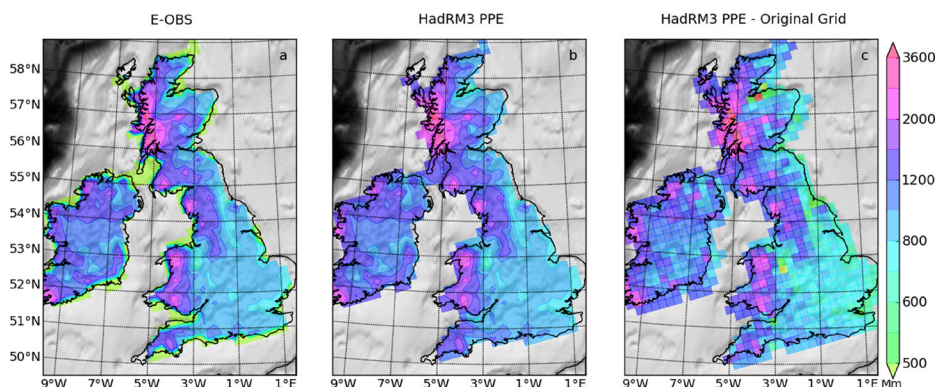


Fig. 1 Annual total precipitation (mm), averaged over 1961–1990, shown for interpolated E-Obs values (**a**) interpolated and ensemble-member averaged HadRM3 PPE values (**b**), and (**c**) ensemble-member averaged HadRM3 PPE values on the original shared grid. Green values in the left-hand pane show the boundary of the E-obs dataset

interpolation difficult), and the potential for changes in observational practice over time, which often introduces breaks and inconsistencies in the record (Hofstra et al. 2009). Given the indices under consideration and the biases in the E-OBS dataset, we might expect positive bias in the number of Dry Days, and negative bias in the occurrence of Plant Heat Stress.

This study does not, however, include any bias correction. Without a singular, consistent, resolution-appropriate, and reliable comparator for the whole domain, uncertainty surrounding observational error is hard to tackle. It is important to correct systematic bias on a per-index basis where possible (Hanlon et al. 2013), and on a per-member basis if perturbed ensembles are used: Different perturbations may produce differing biases. The indices presented here are derived from daily rainfall totals and maximum, minimum and mean temperatures. Correcting those values may help to offset biases in derived indices, but here we show that there are biases in the Start of Field Operations and Growing Season Length indices, both dependent on an accurate representation of seasonal variability. The addition or subtraction of a given value to daily temperature values may or may not fully resolve these issues unless using a method as shown in Hanlon et al. (2013).

2.4 Climate model data

The future-period data used here, the HadRM3 PPE, is an ensemble of regional climate model runs from 1950 to 2099 over Europe, developed by the UK Met Office for the UKCP09 project, driven by a ‘medium’ emissions scenario (SRES A1B) (Nakicenovic and Swart 2000). The HadRM3-PPE is made up of eleven different runs driven by HadCM3 Global Circulation Model (GCM) boundary conditions (Gordon et al. 2000). Each member of the ensemble is characterised by its climate sensitivity; the simulated warming at equilibrium when atmospheric CO₂ is doubled (Murphy et al. 2007). Each regional ensemble member inherits perturbations to the model physics from the coupled model that supplies its boundary condition (Murphy et al. 2007). One version (‘afixa’; Table 2) uses ‘unperturbed’ atmospheric parameterizations. The other ten use slight variations on model parameters in, amongst others, convective parameterisation and cloud microphysics.

These ensemble members together produce an estimate of potential uncertainty. They have been designed to produce a broad sampling of future possibilities sampling both chaotic

variability and uncertainty in climate modelling (Sexton et al. 2010), but should not be considered individually. With more ensemble members, a greater range of futures could be described, but deeper, structural, uncertainty would remain. Probabilistic output is available, but has not been used due to lack of spatial coherency (Sexton et al. 2010). Despite that particular limitation, the probabilistic UKCP09 Climate Projections provide a framework for the development of many impacts-relevant, ultimately HadRM3 derived, approaches (Murphy et al. 2009; Prudhomme 2012).

3 Results

Here we show an analysis of average values of each index, then examine the distributions and finally consider ensemble-averaged maps for each index. For each of these we compare the simulated 1961–90 values with E-OBS, and consider future change in the model projections.

3.1 Validation of indices

On average, historical model biases (vs. observed) are small (too short) for Growing Season Length (GSL) and (too late) Start of Field Operations (SFO) (Table 2). By contrast, there are substantial systematic historical model biases in the number of Dry Days (much too few), Air Frosts (too high a degree), and Plant Heat Stress (too large) (Table 2). Biases in the latter two are likely due to both exaggerated model temperature extremes (Ho 2010), and a reduced range of observed temperature values (Haylock et al. 2008). Given that interpolation issues (i.e., underdispersion; Wilks 2011) in the construction of the E-OBS data set (Haylock et al. 2008) are unlikely to affect the order of events throughout the year, it seems likely that late Start of

Table 2 Sensitivities (Met Office 2012), given in Kelvin, and biases in HadRM3 PPE ensemble members in the units shown in Table 1

RCM run	Sensitivity of driving model (K)	Historical (1961–1990) mean					Future (2061–2091) mean - historical				
		AF	DD	GSL	PHS	SFO	AF	DD	GSL	PHS	SFO
afixa	2.6	−294	113	202	13	85	+184	+1	+59	+30	−34
afixc	2.8	−413	126	202	17	94	+265	−16	+47	+16	−43
afixh	3.4	−329	116	189	19	90	+190	−7	+53	+25	−32
afgex	3.5	−276	103	202	9	82	+195	−6	+69	+29	−38
afixj	3.9	−221	119	210	13	72	+145	+2	+60	+24	−26
afixi	4.4	−251	127	202	24	81	+180	−7	+70	+29	−41
afixk	4.4	−203	115	212	20	73	+136	−3	+60	+36	−29
afixm	4.5	−320	119	207	15	77	+230	+4	+67	+42	−35
afixo	4.8	−230	116	217	17	77	+166	+1	+61	+42	−33
afixl	4.9	−244	106	208	14	79	+190	−5	+74	+41	−42
afixq	7.1	−248	122	218	19	67	+176	+7	+66	+42	−29
OBS	—	−178	279	220	1.3	72	—	—	—	—	—

Historical (1961–1990) biases are shown against observational means, both averaged over the UK. Red values are hot/dry, blue values are cold/wet, grey values are insignificant using a Wilcoxon signed-rank test (Wilks 2011). Future change is calculated as mean values for 1961–1990, subtracted from mean values for 2061–2090

Field Operation figures and mildly short Growing Season Lengths describe modelled winters that are too long and too cold, and modelled summers that are too short.

Rivington et al. (2008b) found that the single member version of HadRM3 generates too many small rainfall events (<0.3 mm), still above our threshold for a “wet day”, compared to the British Atmospheric Data Centre’s daily precipitation record (<http://badc.nerc.ac.uk/home/index.html>). This is a well known issue with climate models (the “drizzle effect”; Prudhomme 2012) leading to an underestimation of Dry Day occurrence, as seen in Table 2. Haylock et al. (2008) suggests that E-OBS has a significant dry bias for extreme precipitation events above the annual 75th percentile, and Hofstra et al. (2009) describe a significant overall dry bias in E-Obs due to over-smoothing. Sources of bias in our Dry Days index are thus difficult to identify. A higher threshold for the index could help to minimise these issues, but even days with low rainfall (rather than none) are important for agriculture. We have used a lower threshold, but recommend that the reader not overestimate the reliability of low-threshold modelled output for dry-day indices.

Aggregated historical bias and climate sensitivity seem largely uncoupled for our indices. We might expect indices that measure temperature magnitudes (PHS) to behave consistently with a warmer model world, but only when considering average changes in Plant Heat Stress from past to future periods, and the first and last five ranked ensemble members as separate groups (mean values of +25 and +41, respectively), can we say that changes might be linked to sensitivity. Regionally averaged temperature is likely to respond strongly to model climate sensitivity, but measures of relatively uncommon events may be more strongly related to internal climate variability. Given a lack of evident relationship with climate sensitivity, the level of aggregation in Table 2, and the small sample size of this analysis, it appears that the variance of a given ensemble member is more likely to be driven by either model noise or internal variability.

3.2 Aggregate change

Dry Days is the only index that shows no significant (spatially aggregated) change across ensemble members (Table 2). Modelled Aggregate Air Frosts decline dramatically from their historical values towards 2061–2091, in most cases by between a half and two-thirds. Growing Season Length increases by around a half again, to take up almost three quarters of the year. Plant Heat Stress occurrences more than double in most members, and triple in those members with high climate sensitivities (over 4.5 °C). Start of Field Operations dates shift back into mid-to-late February for the cooler nine members, and early February for the warmest two. These changes are vague by necessity, given that spatial aggregation over the UK removes regional relevance, no single ensemble member is any more likely than any other, and that these are also temporally aggregated averages. They are useful as a rough estimation of changes for the whole of the UK, for the second half of this century, and for a subset of possible futures, but little else. To gain further information we must disaggregate Table 2 into the relevant distributions, or with a greater degree of spatial granularity.

3.3 Distributions

Probability Density Functions (PDFs) are frequently used within climate modelling (e.g. Wilks 2011). Here they allow us to disaggregate bias for a greater level of analysis (Fig. 2). They are used to show not just the ‘location’ (i.e., the mean, Table 2), but also the scale (range) and shape (distribution) of each member against observational data for the past, along-side

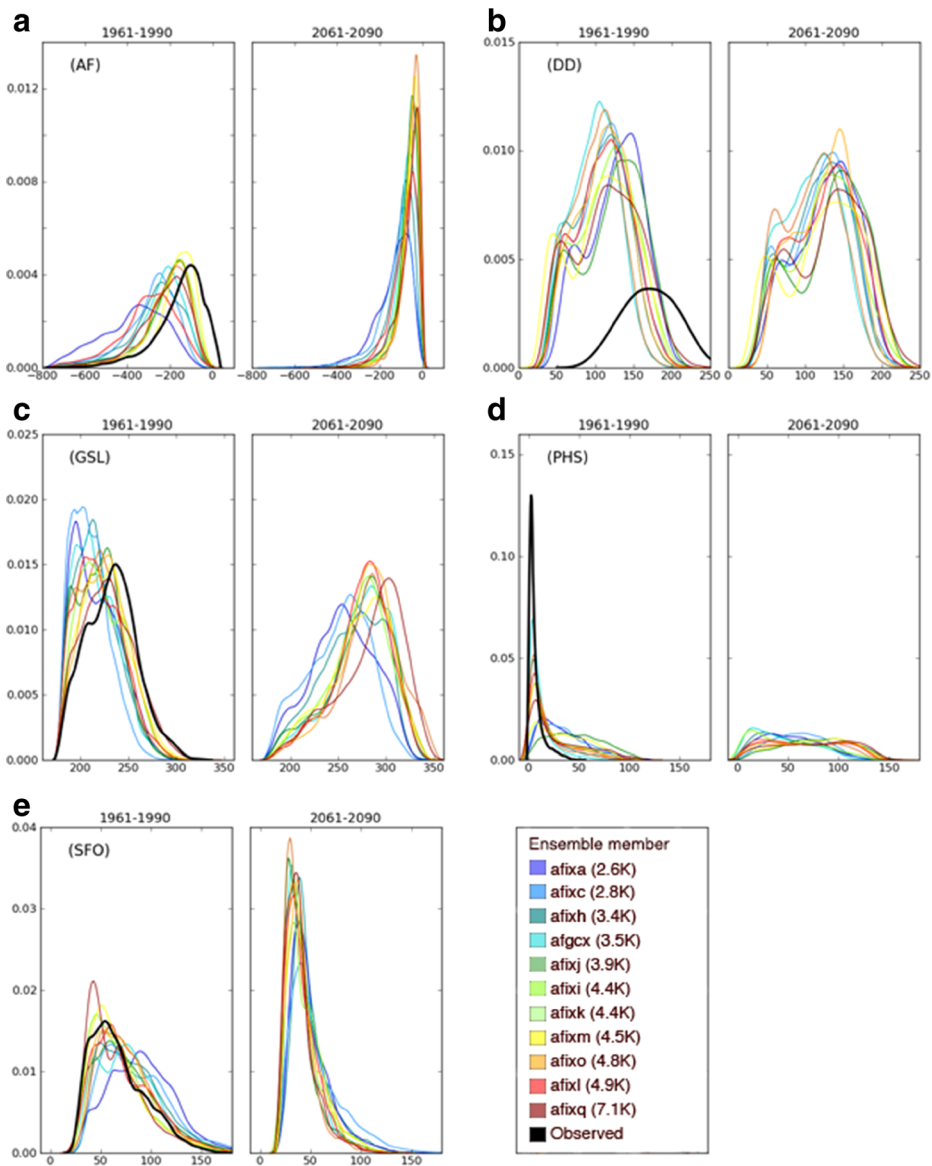


Fig. 2 PDF plots of the indices given in Table 1 (a- Accumulated Frost, b- Dry Days, c- Growing Season Length, e-Plant Heat Stress, 5- Start of Field Operations). Plots show results for each ensemble member, with warmer colours representing greater climate sensitivity (Table 2), for both the past (1961–1990, *left*) and future (2061–2091, *right*). Thick black lines (*left only*) show observational results

behavioural shifts for the future. Note that these plots include all years and grid points for the target region over the historical or future periods. This allows us to assess bias in the tails, and whether or not uncertainty may expand or shrink over time through ensemble convergence or divergence. If the PDFs show less (more) agreement into the future, then our sampled futures are diverging (converging).

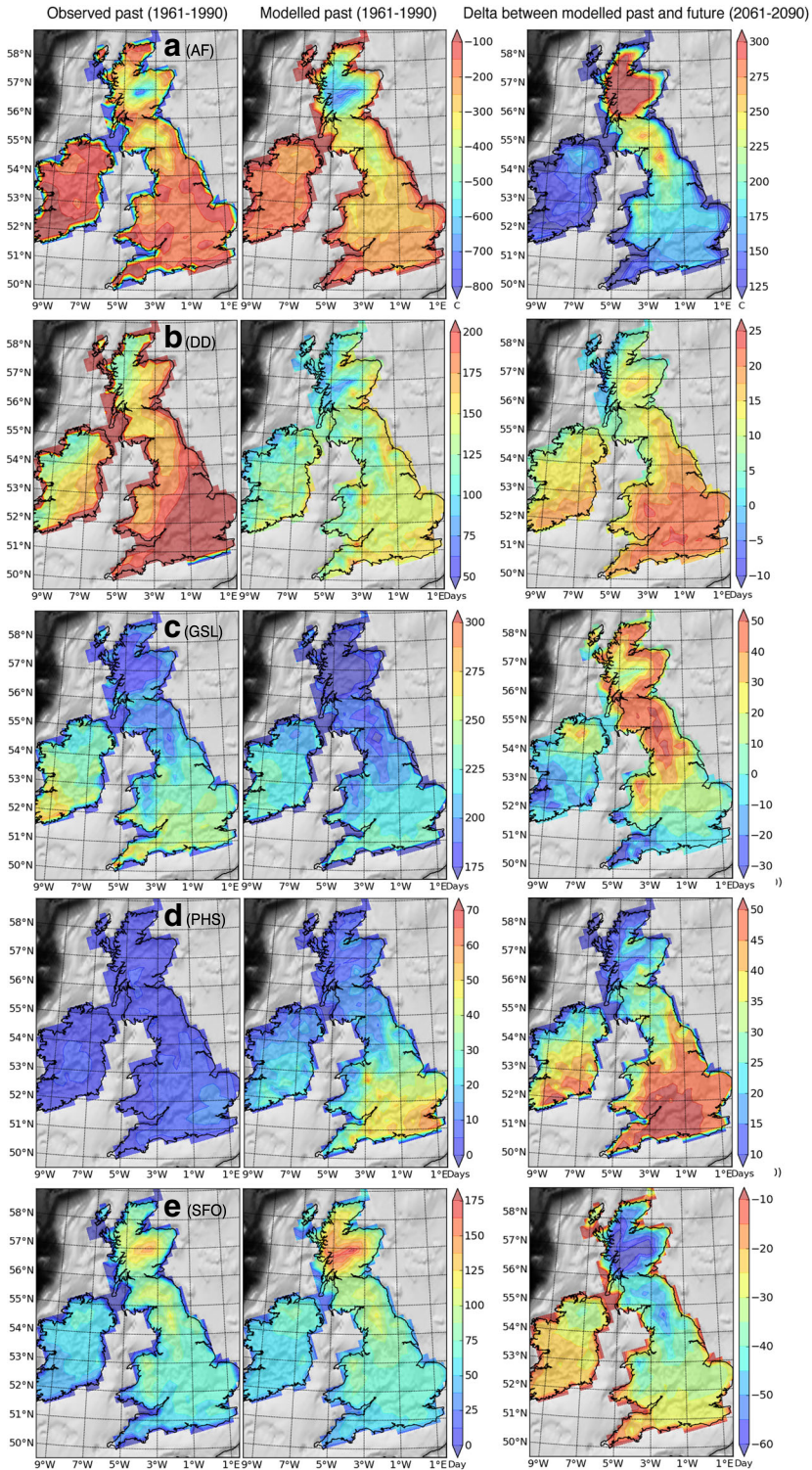
Both Accumulated Frosts (AF) and Start of Field Operations (SFO) convergence into the future, with a clear tendency toward a lack of future frost (Table 2). Warmer members have a tendency for a narrower distribution and fewer years with many frost days (Fig. 2a). This shift in behaviour is inverted for SFO, describing regimes that are more likely to possess start dates within the first three months of the year. Later (upper tail) dates shift earlier more for warmer members than cooler members. This lengthening of field operations may influence field preparation dates (e.g. tillage) but might also increase the risk of soil compaction if early operations are conducted in wet conditions. Compaction may lead to induced nutrient deficiency, and thus an ultimate yield reduction (Lipiec and Stepniewski 1995). Both AF and SFO show distributions that smooth into unimodal distributions and converge into the future.

Ensemble members all show a mean increase in Growing Season Length of around two months. Distributions of GSL show little convergence for 2061–90 and the future distributions are not well represented by simple shifts of one another (Fig. 2c). By 2061–2090 the coolest three ensemble members and the warmest one are distinct from the rest of the ensemble (smaller and larger increases, respectively, limiting convergence), but most members possess many more years or locations for which the growing season is the entire year. Nearby regions which display a year-long growing season include Portugal and Galicia. Longer growing seasons may allow for a greater diversity of crops (including those with long maturation periods), and the potential for multiple harvests on the same land. Conversely, both irrigation needs and the risk from invasive species, pests and pathogens may increase (EPA 2013).

In all ensemble members (but not observations) Simulated Dry Days (DD) possess a bimodal distribution with a peaks at both 120 and 60 days. This second peak is likely due to overly wet model results for north-western Ireland and western Scotland (Fig. 3). The most likely reason for this under-representation of dry days is a tendency for the model to over-estimate drizzle, as described above. Although the 60-day peak remains relatively static into the future, the 120-day peak increases towards 130 days. Biases appear similar throughout the distribution (as seen in Table 2) and have no apparent relationship with climate sensitivity. In terms of impact, an increase in long-lived dry conditions is also likely to increase the need for irrigation, particularly if compounded with a coterminous increase in Growing Season Length. We have repeated a selection of our Dry Days results for a 1 mm threshold (Online Resource 1), which shows that modelled results are much closer to observations when the daily threshold is increased. However, bimodal behaviour is still apparent and there remains no evident relationship with climate sensitivity. Given that the smaller (100 day) peak is poorly represented in the 1.0 mm plots while the larger (200 day) peak is only slightly underestimated, an excess of drizzle in the model seems likely. Although dry day periods are longer with a larger threshold, there is still little change from the past to future periods.

Many of the Plant Heat Stress (PHS) historical PDFs peak close to zero days, including the observational PDF, but some show a wider range. Future changes are generally towards a broader distribution with no zero-days peak. The future-period PDFs show a tendency for warmer-world members to have a broader spread and greater maxima than the cooler members. There are many locations or years for which PHS does not occur in the past, and this is less evident in the simulations, much less true into the modelled future, and even less so for warm members than cool ones. As suggested above, PHS is more sensitive to changes in model physics than the other indices. Even so, a future in which every year shows some degree

Fig. 3 Observational (past, 1961–1990, *left*) and ensemble-average modelled (past, 1961–1990, *centre*) maps for each of the indices in Table 2, shown with delta (change, *right*) maps calculated as past model values subtracted from future model values



of PHS may require complex adaptation strategies, possibly including crop breeds with a greater thermotolerance (Wahid et al. 2007).

Growing Season Length and Accumulated Frosts both shift from a complex, multi-modal distribution towards a unimodal peak, unlike either Dry Days or Plant Heat Stress. Although both Accumulated Frost and Dry Day index distributions narrow into the future, in the former case it is with a shift of mean values towards less frosts, and in the latter, with only a slight change in the mean towards drier conditions. The regional model ensemble (Table 2, Fig. 2) suggests a future UK with fewer frosts (Fig. 2a), fewer years with a large number of frosts (Fig. 2a), and an earlier start to field operations (Fig. 2e). It is a future with more dry days (Fig. 2b), more hot days (Fig. 2d), and a much longer growing season, with 10 and 11 month growing seasons becoming more common toward the end of the century (Fig. 2c).

3.4 Spatial analysis

End-users of climate model data are often most interested in the magnitude of the change that they are likely to experience (see above), types of climate change that are specifically relevant to their needs (e.g. the indices used here) and changes that are specific to their geographical region of interest. Maps of difference over time directly address these three points, and can also provide information about regional change over time.

Maps of Accumulated Airfrost days (Fig. 3a) illustrate how aggregation over a wide area can skew results. The spatial pattern of accumulation is such that although a slight latitudinal effect is apparent, the Scottish Highlands are the main feature in both periods. The Highlands have historically been the region most prone to frost (Fig. 3a), and is projected to see the greatest frost reduction (by in excess of 300 degree days over the year), compared to relatively little change in the south west of England and Ireland (less than +170).

Systematic bias in the number of Dry Days (DD) is also evident in the spatial maps (Fig. 3), as is the double peak behaviour seen in its PDF (Fig. 2). DD increase across Great Britain and Ireland, with the largest increases in the SE, but reductions in parts of coastal NW Scotland (Fig. 3b). The patterns between observational and modelled pasts are consistent, but projected future values (change plus modelled past) are smaller than historical observed values. Stand-alone maps of gridded observational data or model output dependent on rainfall may be suspect, but changes from one period to another might be more reliable. Constant biases may cancel out unless they arise from issues of non-stationarity. Here, DD are shown to increase by over 25 days in the south-east, of England and to decline by 10 in north-western Scotland. As with the PDF plots (Fig. 2), an increase in threshold to 1.0 mm/day (Online Resource 1) provides a much closer fit between modelled and observed results. The change plot for the future period is similar to that for the 0.2 mm/day threshold, although with less intense increases in the south of England, Wales, and Ireland (+15) and a southerly shift in the wetter (−10) band from the coastal N and NW of Scotland to the western and northern Highlands.

For Growing Season Length (Fig. 3) the historical period shows a combination of latitudinal and altitudinal effects, with GSL higher toward the south (around 250 days) and for lower altitudes, than the north and higher altitudes (~190 days). The change map shows a significant increase in GSL across most of the UK (+20–50 days), with less in the highlands (+10–30), and an unexpected decrease in the south-west of England, Ireland, and Wales (−10–30), these changes compliment those in Accumulated Air frost, but the south western decrease is difficult to explain.

PHS values for the modelled past are significantly overestimated in the south of Ireland and England (by ~25–55 days), which displays values at the upper end of the PHS distribution (Fig. 2d), but not in the north. The lower projected Plant Heat Stress values for Scotland (+10–

25) may therefore be more reliable than the higher values for the South of England (+40). Although threshold based indices give no indication of changes in the distribution below a given value: There may be a progressive bias where higher values are inflated more than lower values; there may be dynamical reasons for a southern over-estimation; or historical modelled values for Scotland might be ‘right for the wrong reasons’. Were northern PHS values robust, however, an additional three weeks of temperatures in excess of 25 °C would be a significant change.

Although significant shifts in Plant Heat Stress are likely to be the most adaptation-relevant result from this study, there are serious questions as to whether or not the model results are fit for purpose. It is clear that the ensemble (averaged over members) overestimates summer high temperatures, and more so in the south than the north. The projected increase in Plant Heat Stress is almost entirely due to an increase in the average of those temperatures (Online Resource 2a), rather than an increase in temperature variability. Taking average summer temperatures for 1961–1990 adjusted with the mean change (‘delta’) between past and future period summers (3.2 °C) and calculating Plant Heat Stress values from the new constructed future temperatures suggests that the model could be corrected with regards to high temperatures, and that simulated changes may be robust (Online Resource 2b). However, this study does not include information on the timing of heat stress, which may be critical in determining crop productivity, and is an important avenue for further research.

The Start of Field Operations is later in the Scottish Highlands (by 25–50 days) than any other part of the UK during the historical period, with the North of England and Mid-Wales showing SFO values around 80–100 (end of March / beginning of April), 50–70 for the south of England and northern Ireland (end of February), and 15–30 for Cornwall and Southern Ireland (January). Delta values fit this pattern, with later starts becoming proportionally earlier. Although modeled SFO values are slightly biased (toward later values) in Scotland, projections show SFO values around two months earlier in the Highlands. For the rest of the UK, values are a month and a half earlier in the north of England, a month earlier throughout southern England and Northern Ireland and two to three weeks earlier for southern Ireland and Cornwall. Those with earlier starts change less, and the variation in start date is likely to diminish across the UK. Although there is not much agreement between the model ensemble members, there is little systematic bias here, relative to observations, on average.

If we assume that land managers alter their habitats to cope with these new conditions (and specifically days of Plant Heat Stress), earlier and earlier shifts in the start of field operations could imply a generally increased capacity, allowing for earlier fertilization, tillage, and sowing. Recent years have, however, shown that heavy winter or spring rainfall can make fields inaccessible even when warm spring and summer conditions prevail. Model projections show that the wettest regions of the UK, specifically western Wales and western Scotland, are becoming wetter still (Online Resource 3a). When looking at annual totals (Online Resource 3b) we can see that increases in the north-west are more than an order of magnitude greater than in the south east. Ekström et al. (2005) show that the magnitude of long duration, high return period extreme rainfall is declining for most of the UK (–20 %), but increasing substantially for Scotland (+30 %). This may be an issue that keeps Scottish land managers from making the most of extended field and habitat access without sufficient drainage.

4 Conclusions

From the results shown above, a significant change in the stresses and challenges experienced by land managers in the UK and Ireland seems likely. Future agro-meteorological conditions

will likely be sufficiently different from current conditions to require substantial changes to land use management practice. With frosts decreasing dramatically, particularly in the highlands, field operations starting earlier across the UK, with greatest change in regions with historically later start dates, and thus longer growing seasons, we might expect the primary productivity of most crops to increase. Over most of the UK the growing season length increases almost two months allowing a near year-long growing season over much of Southern England.

Changes in growing season length occur along with increases in dry days, and more significantly, a dramatic increase in the number of days of heat stress. The possibility of more than an additional month of withering heat and days without rain in the south, and an extra three weeks in parts of Scotland, has serious repercussions for the kinds of crop or habitat that will thrive in any given part of the UK. Combined with a lack of frosts for both those species that require a few days of hard winter (i.e., vernalisation), and for pests which are normally limited by cold conditions, we might expect agricultural changes in the next 20 years as a function of shifts at both ends of the seasonal temperature cycle.

Regional climate models are still being developed and their (less than perfect) results require both caveats and explanation. These are many issues at play in the interpretation of regional climate model results. The scale of data is important, and must be relevant to end-user needs. Data that are at too low a resolution will miss the full range of values due to sampling issues, and where they are generated from a model, will fail to represent the relevant dynamical processes. Observed data that, by their nature, require interpolation may not be without their own biases, making the validation of models difficult. This is true at both the regional scale (see above) and at the global level (Wan et al. 2013). Even where primary variables such as temperature and rainfall are well replicated by models, indices derived from those variables may possess their own (potentially independent) biases, particularly when considering indices that represent time-order or occurrence.

With respect to the unique challenges posed by climate model ensembles, we can see from Fig. 2 that single ensemble members should not be assessed in isolation. Ensemble members with a greater degree of sensitivity can be seen to undergo larger shifts for derived indices over time, in ways that may be geographically uneven. This is likely to obscure the potential for relationships between model sensitivity and projected change when aggregated across larger regions (such as the UK).

Model bias and model sensitivity are not necessarily consistently linked. In general, model bias has a far greater degree of complexity than allowed for by a single aggregate metric of change. Bias correction is important, but must be handled with care and with respect to the possibility of events occurring too early or too late. Distribution changes are difficult to explain or validate, but they have important consequences for studies that try to predict particular variables directly (Accumulated Frosts and Start of Field Operations, in this case).

Where known systematic biases exist, and those biases vary from one region to the next, maps of change may be among the most useful tools for the presentation of climate change. These maps are more robust than many other forms of presentation, simply because they are essentially a form of bias correction in their own right, with systematic, geographically consistent biases dealt with by subtraction.

If researchers or land-managers are considering the deployment of dynamic, deterministic, crop-yield modelling tools we would suggest that where climatic drivers are utilised, they are handled with care. The climate may change significantly (in the UK at least) in ways that are directly relevant to agricultural stake-holders. Changes are likely to challenge crops in terms of heat-tolerance, water requirements, timing, and potentially pest prevalence, and are likely to come with complex biases that vary from one driver to the next.

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